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COVID-19 morbidity and mortality in U.S. meatpacking counties[☆]

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ABSTRACT

In this paper, we investigate the extent to which the presence of a large meatpacking (i.e., beef, pork, and broiler chicken) plant has affected county-level COVID-19 transmission dynamics. We find that—within 150 days after emergence of COVID-19 in a given county—the presence of a large beef packing facility increases per capita infection rates by 110%, relative to comparable counties without meatpacking plants. Large pork and chicken processing facilities increase transmission rates by 160% and 20%, respectively. While the presence of this type of industrial agricultural facility is shown to exacerbate initial disease transmission affecting large numbers of individuals in the community, over time daily case rates converge such that rates observed in meatpacking- and non-meatpacking counties become similar. In aggregate, results suggest that 334 thousand COVID-19 infections are attributable to meatpacking plants in the U.S. with associated mortality and morbidity costs totaling more than \$11.2 billion.

1. Introduction

During the novel Coronavirus Disease 2019 (COVID-19) outbreak, meatpacking operations in the United States were declared to be critical infrastructure and essential to national security. The demand for meatpacking facilities to remain operational has directly impacted more than a half million employees (Waltenburg et al., 2020) and has been alleged to have increased transmission and infection rates in host communities (Bagenstose et al., 2020; Douglas and Marema, 2020). Considering COVID-19 case rates over time (Fig. 1) provides *a priori* evidence that counties with beef, pork, and chicken processing facilities have elevated infection rates. Based on such data, “back-of-the-envelope” estimates suggest increases in county-level infection rates, associated with the presence of a meatpacking facility, between 75% (Bagenstose et al., 2020) and 400% (Douglas and Marema, 2020). To date, available studies fail to account for county-level demographic, economic, education, and structural characteristics that are known or suspected to influence COVID-19 transmission and ignore the staggered timing of viral diffusion across the nation. A recently published paper by Taylor et al.

(2020) is the single exception to date. While controlling for some county-level demographic information, the authors find that early in the pandemic (i.e., through July 2020) meatpacking operations increased transmission rates by 51% to 75%.¹

The meatpacking industry in the United States employs approximately 525,000 people (Waltenburg et al., 2020); representing 30% of food and beverage manufacturing employees in the country (USDA, 2018). Workers are concentrated in large facilities including 39 beef packing plants, 31 pork processing facilities, and 139 broiler chicken processing operations (Fig. 2) (FSIS, 2020). The most current estimates available from the Centers for Disease Control and Prevention (CDC) indicate 16,233 confirmed COVID-19 cases among meatpacking plant employees through May 31, 2020; an infection rate of 9.1% (Waltenburg et al., 2020). In addition, nearly 1,000 (roughly 15%) U.S. Department of Agriculture (USDA) Food Safety and Inspection Service (FSIS) employees, assigned as inspectors at meatpacking facilities, were off the job with coronavirus-related illnesses or under preemptive quarantine (Shanker et al., 2020).

The substantial overlap between racial disparities in COVID-19-

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¹ The impacts found by Taylor et al. (2020) are lower than our 150-day estimates for a number of reasons. First, the empirical specifications used in this work produce a single point estimate (i.e., COVID transmission effect) for beef, pork, and broiler plants. Given that broiler plants had substantially lower transmission rates, this average treatment effect is attenuated compared to our species-specific estimates. Second, Taylor et al. (2020) do not harmonize the start date of first COVID-19 case in a county. As such, they are not able to consider counties at the same evolutionary stage of COVID-19 case onset.

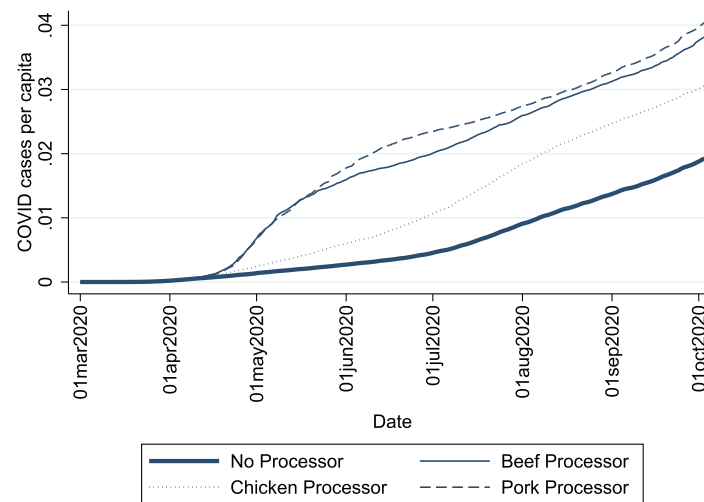


Fig. 1. COVID-19 cases per capita in large-meatpacking vs. non-meatpacking counties. Source: Data on the location of large meatpacking facilities are obtained from Food Safety and Inspection Service [FSIS \(2020\)](#). Data on daily confirmed COVID-19 cases are obtained from [USAFacts \(2020\)](#).

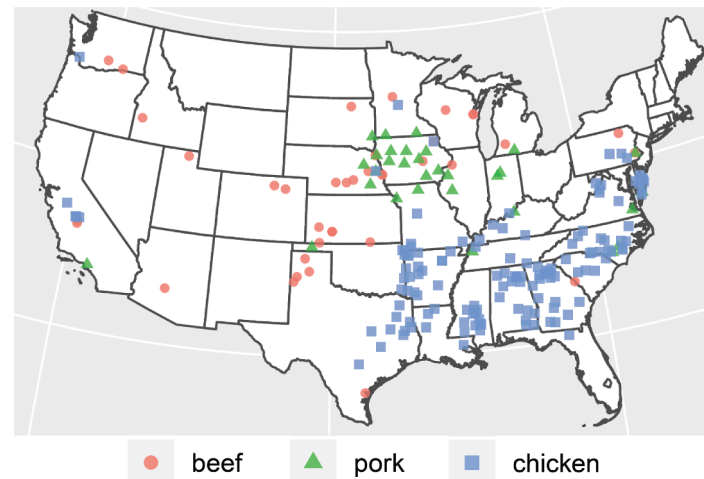


Fig. 2. Location of large beef, pork, and chicken processing plants. Source: Data on the location of large meatpacking facilities are obtained from Food Safety and Inspection Service [FSIS \(2020\)](#).

related health impacts and the demographic composition of meat packing plant workforces is additional cause for concern. The CDC has documented the disproportionate burden of COVID-related illnesses and deaths borne by ethnic minorities in meatpacking operations; 87% of the confirmed cases have occurred among racial minorities with Hispanic, Black, and Asian workers disproportionately affected in this occupational environment ([Waltenburg et al., 2020](#)).

A variety of environmental and infrastructure-related factors contribute to increased transmission rates observed within meatpacking plants; with common operational characteristics creating risk of super-spreading events ([Guenther et al., 2020](#); [Middleton et al., 2020](#)). Droplets and aerosols are believed to be the primary transfer mechanisms for the COVID-19 virus. While droplets rarely travel more than 2 meters in indoor settings, aerosols have the ability to carry the virus over extended distances under specific environmental conditions, many of which are present in processing plants. Low temperature, low humidity, low air exchange rates, and constantly re-circulated air have been shown to increase the distance of aerosol transport of the virus to 8 meters or more ([Guenther et al., 2020](#)). Beyond airborne transport, metallic surfaces, often used in packing operations to facilitate cleaning, create vast surface areas where the virus is able to persist and be transported when rinsed with water ([Middleton et al., 2020](#)). Work-related conditions also

contribute to elevated levels of transmission within a facility; congregate work and break areas limit the ability of workers to maintain adequate distance and the pace and physically-demanding nature of work makes adherence to face-coverage mandates challenging ([Dyal et al., 2020](#); [Guenther et al., 2020](#)).

Socio-political factors likely influence disease transmission as well. Many meatpacking workers live in multi-generational settings and often share transportation to and from work, increasing transmission risks both inside and outside of the workplace. Undocumented immigrants workers, which comprise a significant portion of meat processing workforces, are more likely to keep working despite illness and infection risks because i) they are not able to access unemployment benefits or economic safety net measures enacted by Congress and ii) those who face tenuous immigration status may fear job loss or deportation if they report or seek treatment for work-related injuries and illnesses ([GAO, 2016](#)). Following President Trump's invocation of the Defense Production Act, some counties and states limited the unemployment benefits that packing plant workers were able to qualify for if they refused to show up to their existing job ([Schlosser, 2020](#)).

The present study utilizes an approach from the emerging economic-epidemiology literature on COVID-19 (e.g., [Desmet and Wacziarg \(2020\)](#), [Mangrum and Niekamp \(2020\)](#)) in order to compare growth

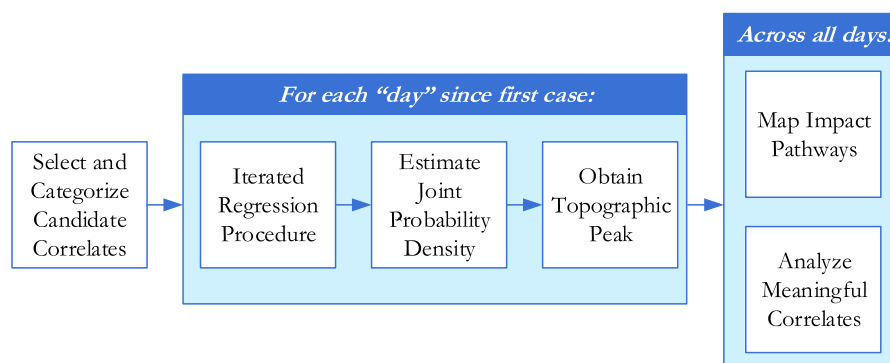


Fig. 3. Schematic representation of topographic regression procedure.

rates in infections per capita by considering counties at the same evolutionary stage of COVID-19 case onset. After harmonizing disease evolutionary stage by location, we construct an econometric model to quantify the impacts of large (i.e., capacity to produce 10 mil lbs or more per month) beef, pork, and broiler chicken processing plant on county-level COVID-19 transmission rates. To do so, we match data on the location of the processing facilities from the Food Safety and Inspection Service FSIS (2020) (Fig. 2) with county-level data on daily confirmed COVID-19 cases between January 22, 2020 and October 3, 2020, obtained from USAFACTS (2020). The “topographic regression” estimation procedure draws on the emerging computational model robustness literature (Sala-I-Martin, 1997; Ortiz-Bobea et al., 2020; Simonsohn et al., 2019). In summary, across all of the 3,405 counties in the continental U.S. each day since the first COVID-19 case in the county, we estimate 62,400 regression specifications (9.36 million regression models in total) in order to estimate the impact that large meatpacking operations have on the transmission evolution and infection rates of COVID-19.

The remainder of the paper is organized as follows. Section 2 describes the evolution of the U.S. meatpacking industry. Section 3 describes our empirical analysis, and Section 4 reports results. Section 5 discusses policy implications and concludes.

2. Evolution of the U.S. meatpacking industry

Several factors, that have manifest over many decades in the 20th century, have worked to shape the industrial meatpacking industry that we know today. First, Iowa Beef Processors (IBP) pioneered “boxed beef” technology; allowing processors to ship cuts of meat ready for consumers as opposed to shipping whole or partial carcasses that required skilled labor (i.e., butchers) for further processing (Azzam and Anderson, 1996; Huffman and Miranowski, 1996). Second, improvements in refrigeration and transportation networks (i.e., trucking and roadways) changed the geographic landscape of meatpacking; with plants moving away from urban centers to rural towns in close proximity to where livestock and poultry were reared (Brueggemann and Brown, 2003).² Third, new plants were located in “right-to-work” states where unions were weaker and less expensive, non-unionized labor was available (Broadway and Stull, 2006).

Meatpacking plant construction and expansion persisted into the 1980s and 1990s with other companies emulating IBP’s approach;

targeting locales for processing plant construction where non-unionized labor supplies were readily available (Brueggemann and Brown, 2003; Champlin and Hake, 2006). These innovations and changes in the industry ultimately culminated in species-specific processing plants with mass production (i.e., “disassembly”) lines predominantly located in rural counties in the South and Midwestern portions of the United States.³

Meatpacking operations built in rural communities expanded low-skilled job opportunities, increased public revenue, and provided stimulus for the development of other directly or indirectly related business sectors in the area (e.g., Huffman and Miranowski (1996), Larry Leistritz and Sell (2001)).⁴ During the period when plants were being constructed, meatpacking represented one of the few sectors that expanded manufacturing positions in rural areas of the country that would have otherwise faced limited opportunities for economic growth (Artz et al., 2007). Proximity to livestock production areas also benefited producers by reducing transportation costs (e.g., road miles, shrink, death loss). However, the presence of packing plants also presented a number of challenges for host communities, including: increased tax burden of public assistance, health care, and schools (e.g., Schlosser (2020)); higher crime rates and arrests for violent crimes and sexually-based offenses (e.g., Fitzgerald et al. (2009)); greater poverty rates (e.g., Artz (2012)); increased housing and rental prices due to shortages (e.g., Broadway (2000)); and a host of environmental concerns primarily focused on odor and surface and groundwater contamination (e.g., Hackenberg (1995)).⁵

Champlin and Hake (2006) characterize the meatpacking industry as having a “...drive to increase the number of unskilled jobs and fill these jobs with immigrant labor” (p. 50). Technological innovations and mechanization (i.e., the disassembly line pioneered by IBP) has facilitated this objective by reducing the number of tasks accomplished by each worker, thereby limiting the training and skill required for any given position.⁶ The shift away from skilled workers toward a low-wage workforce has shifted the racial and ethnic composition of packing plant workforces; with foreign-born immigrant labor from Mexico accounting

³ The poultry processing industry is concentrated in the South with Arkansas, Georgia, Alabama, and North Carolina accounting for the majority of broiler chicken slaughter. Beef and pork processing are concentrated in the Midwest portion of the United States.

⁴ Because of these benefits many rural communities, in an attempt to attract packing plants, provided tax incentives and public investment in infrastructure (Broadway, 2000).

⁵ The co-location of feedlots, hog-raising, and broiler-rearing operations and meatpacking plants has exacerbated the environmental concerns about dust, odor, and surface and groundwater throughout the supply chain (Broadway, 2000).

⁶ To date, variation in animal size, frame, and weight, has limited the incorporation of technology into meatpacking plants that would act as a substitute for labor (Hennessy, 2005).

² Broadway (1998) shows that most towns where IBP constructed packing plants had populations of less than 25,000 people. IBP’s flexibility in selection of plant locations also allowed the company to secure tax breaks and other incentives by generating competition among different states or counties (Brueggemann and Brown, 2003). Attracting agricultural processing operations was a popular strategy for rural communities who viewed meatpacking as a good fit for agriculturally dependent regions (Artz et al., 2007).

for extremely high percentages of positions (Champlin and Hake, 2006). Immigrant workers, particularly those who are less skilled and lack education, are less able to exercise their rights and have substantially less bargaining power and ability to organize or unionize. In addition, high levels of employee turnover in the industry—80 to 100% per year—exacerbate workforce requirements and perpetuate the industry's aggressive recruitment of foreign-born unskilled labor (Champlin and Hake, 2006).

3. Methodology

We construct an econometric model to quantify the impacts of large beef, pork, and broiler chicken processing plant on county-level COVID-19 transmission rates. The USDA Food Safety Inspection Service (FSIS) characterizes “large” plants as those with production capacity greater than or equal to 10 million pounds per month.⁷ To do so, we match data on the location of the major beef, pork, and broiler chicken processing facilities from FSIS (2020) (shown in Fig. 2) with county-level data on daily confirmed COVID-19 cases between January 22, 2020 and October 3, 2020, obtained from USAFACTS (2020). We develop a “topographic regression” estimation procedure that draws on the emerging “computational model robustness” literature (Sala-I-Martin, 1997; Ortiz-Bobea et al., 2020; Simonsohn et al., 2019).

The schematic diagram in Fig. 3 describes the approach. Our six-step procedure is as follows: (1) we group candidate controls into seven categories; (2) we estimate the 62,400 iterated regression specifications for each day since the first case; (3) we estimate the joint probability kernel density for “impact” coefficient and statistical significance; (4) we take the topographic peak (i.e., “most likely” combination) of impact coefficient and significance, estimated via joint probability kernel; (5) we combine the topographic peaks for each day since first case to map the impact pathway; and (6) we perform a post-estimation analysis to assess the extent to which inclusion (or exclusion) of individual correlates meaningfully affects our estimates of impact.

A variety of factors are known or suspected to influence county-level COVID-19 transmission rates. We begin by collecting 49 candidate correlates that are known or suspected to influence disease spread. These candidate correlates (listed in Table 1) are obtained from various sources, including the Economic Research Service (ERS), Rural Atlas (ERS, 2020), Robert Wood Johnson (RWJ) Foundation County Health Rankings (RWJ Foundation, 2020), National Alliance of Counties (NACO) (NACO, 2020), and Stanford University (Tay, 2018). We group these factors into seven categories, including (1) critical controls, (2) county structural characteristics, (3) county demographics, (4) county economic characteristics, (5) county education characteristics, (6) county health characteristics, and (7) meat processor indicator variables.

3.1. Iterated Regression Procedure

Having grouped our candidate correlates into these six categories, we next estimate a series of regressions to compare growth rates in infections per capita, considering counties at the same evolutionary stage of the disease. To do so, we all take all observations occurring t days since the first confirmed COVID-19 case. For this set of observations, we estimate the following series of regressions:

Table 1
Classification and description of variables.

Variable	Units	Source
Dependent Variable		
COVID cases	per capita	USAFacts
Meat Processor Indicators		
Beef	indicator	FSIS
Pork	indicator	FSIS
Chicken	indicator	FSIS
Critical Controls		
County Emergency Declaration	indicator	NACO
County Safer-at-home Declaration	indicator	NACO
County Business Closure Declaration	indicator	NACO
State Climate	indicators	USAFacts
Structural Characteristics		
Nursing Homes	number of establishments	Rural Atlas
Correctional Employees	number of employees	Rural Atlas
Land Area	square miles	Rural Atlas
Rural Urban Continuum	continuous	Rural Atlas
Nonmetro	indicator	Rural Atlas
Micropolitan	indicator	Rural Atlas
Retirement Destination	indicator	Rural Atlas
Non-core	indicator	Rural Atlas
Metro Adjacent	indicator	Rural Atlas
Demographic Characteristics		
Population Density	people per sq mile	Rural Atlas
Average Household Size	number of people	Rural Atlas
Int'l Migration Rate	continuous	Rural Atlas
% of Household, Non-English	% of population	Rural Atlas
% Under 18	% of population	Rural Atlas
% 65 and Older	% of population	Rural Atlas
% Hispanic	% of population	Rural Atlas
% Foreign Born	% of population	Rural Atlas
% Born in MX	% of population	Rural Atlas
% Non-White	% of population	Rural Atlas
% GOP Voters	% of votes in 2016 pres. election	Stanford
Economic Characteristics		
Unemployment Rate	% of total workforce	Rural Atlas
Median Household Income	USD	Rural Atlas
Per Capita Income	USD	Rural Atlas
% in Poverty (all ages)	% of population	Rural Atlas
% Employed Agriculture	% of total workforce	Rural Atlas
% Employed Manufacturing	% of total workforce	Rural Atlas
Economy Type	categorical	Rural Atlas
Farming Dependent County	indicator	Rural Atlas
	indicator	

(continued on next page)

⁷ These data include “kill” plants (i.e., processing plants that slaughter animals) and are not inclusive of plants that are solely responsible for further processing.

Table 1 (continued)

Variable	Units	Source
Manufacturing Dependent County		Rural Atlas
Educational Characteristics		
% of adults w/o HS diploma or GED	% of people over 25	Rural Atlas
% of adults w/ some College	% of people over 25	Rural Atlas
% of adults w/ College Degree	% of people over 25	Rural Atlas
Health Characteristics		
% in poor health	% of adults	RWJ
Physically Unhealth Days	Days per month	RWJ
% Smokers	% of adults	RWJ
% Obese	% of adults	RWJ
Food Environment Index	0–10 Scale	RWJ
% Inactive	% of adults	RWJ
% Excessive Drinking	% of adults	RWJ
% Uninsured	% of adults	RWJ
Primary Care Per Capita	primary care physicians per 100 k people	RWJ
% Flu Vaccinated	% of adults	RWJ
Air Pollution	Daily fine particulate matter/meter ³	RWJ
% Severe Housing Problems	% of adults	RWJ

$$T_{it} = \alpha_i + \begin{bmatrix} BEEF_i \\ PORK_i \\ CHICKEN_i \end{bmatrix}' \beta_t + \mathbf{X}_{it}' \Gamma_t + \begin{bmatrix} STRUCTURAL_i \\ DEMOGRAPHIC_i \\ ECONOMIC_i \\ EDUCATION_i \\ HEALTH_i \end{bmatrix}' \lambda_t + e_{it} \quad (1)$$

where dependent variable T_{it} is the number of confirmed cases per capita in county i as of t days following the first confirmed case.⁸ Variables $BEEF_i$, $PORK_i$, and $CHICKEN_i$ are indicators that take value one for counties in which large processing facilities are located, and equal to zero otherwise.

Vector \mathbf{X}_{it} is the set of critical controls. These controls include indicator variables for each state (to control for state-level policies and compliance with social distancing mandates). Additionally, we include three dummy variables which indicate whether, at time t , the county had enacted, respectively, a COVID-19 emergency declaration, a shelter-in-place restriction, and/or a mandatory business closure policy. Finally, we include in the set of critical controls a series of indicators for the 18 Köppen climate regions to capture the effects of climate on disease transmission.

⁸ We also investigate whether counties with meatpacking plants identify their first case of COVID-19 earlier (or later) than other counties. To do so, we estimate our topographic regression model, substituting as the dependent variable the date of the first case—programmed as the number of days since Jan 22, 2020 (the date of the first confirmed COVID-19 case in the U.S.). This analysis is summarized in Appendix Fig. A6, where the reported results are the topographic peaks from our iterated regression procedure. As shown in the Figure, holding other factors constant, meatpacking counties did experience their first cases sooner than their non-packing counterparts. The presence of a beef packing county corresponds to the identification of the first COVID-19 case nine days earlier than comparable non-packing counties (statistically significant at 95%). Similarly, the first case arrives in pork and broiler packing counties six days and three days earlier than non-packing counties (both statistically significant at 95%). We do not believe these biases our estimates. While these results are statistically significant, they are probably not of substantial economic consequence. For pork and chicken, for example, the impact is less than one week. Moreover, our approach of beginning our estimation of each county on the day where the first case is diagnosed is employed to harmonize the starting point of viral transmission in the county. As such, the date/time that the virus arrived will not impact our results as we have harmonized the start date across all counties in the U.S.

We adopt an iterative approach for the variables assigned to the five covariate categories $STRUCTURAL_i$, $DEMOGRAPHIC_i$, $ECONOMIC_i$, $EDUCATION_i$, and $HEALTH_i$. For a given specification, we select one variable out of each category. In the next iteration, we re-run the model, but change the selected variable for one of the categories. We estimate the model for all combinations of variables within these five categories. We also include, in each of the five covariate categories, a specification where the category is excluded from the model.

As shown in Table 1, the $STRUCTURAL_i$ category includes 9 candidate correlates (plus the exclusion); the $DEMOGRAPHIC_i$ category has 11 candidate correlates (plus the exclusion); the $ECONOMIC_i$ category includes 9 candidate correlates (plus the exclusion); the $EDUCATION_i$ category includes 3 candidate correlates (plus the exclusion); and the $HEALTH_i$ category includes 12 candidate correlates (plus the exclusion). Thus, for each day t since the first confirmed case, this process results in 62,400 (i.e., $10 \times 12 \times 10 \times 4 \times 13$) unique regression specifications. We repeat the procedure for all t from the day of the first confirmed case (i.e., $t = 1$) to the 150th day following the first case ($t = 150$) for a total of 9.36 million regressions.⁹ We estimate each model for 3,045 counties in the contiguous U.S. with a final dataset that contains 445,224 observations. Summary statistics for left- and right-hand-side variables are reported in Appendix Table A1.

3.2. Inference via topographic peak

After estimating the iterated regressions for a given time t , we estimate the statistical topography (i.e., the joint probability density) for the point estimate $(\hat{\beta}_t^i \forall i \in \{\text{Beef, Pork, Chicken}\})$ and the corresponding p -value for each of our variables of interest across all model specifications. These joint probability densities are estimated using an Epanechnikov kernel. For each i , we then obtain the topographic peak (denoted $\hat{\lambda}_t^i$) of the estimated probability density function for the set $(\hat{\beta}_t^i, p^i)$. This peak constitutes the most likely estimate of the true impact of a packing plant on disease transmission and the statistical precision with which this impact is estimated as of time t . As with the iterated regressions, we repeat this procedure for all times t from the day after the first confirmed COVID-19 case ($t = 1$) through the 150th day ($t = 150$). The concatenation of these topographic peaks $(\hat{\lambda}_1^i : \hat{\lambda}_{150}^i)$ gives us a non-parametric estimate of the impact of packing plants on county-level disease dynamics. We also calculate these topographic peaks for each control variable used in the analysis.

We further use estimates $\hat{\lambda}_{150}^i$ to assess the county-level, state-level, and nationwide disease burden created by packing plants based on the concept of the statistical value of a life (Dockins et al., 2004). Because we have calculated impacts $\hat{\beta}_t^i$ on a per-capita basis, the disease burden created by a packing plant in a given county i is calculated as the population in the county multiplied by the per capita impact estimate as of the 150th day since the first case. For each infection attributable to a meatpacking facility, we assign a “cost” to account for approximately three weeks of lost wages (from the perspective of the infected individual) and lost economic productivity (from the perspective of the county). We obtain this estimate by multiplying the number of cases caused by a plant by \$14.05 times 8 h per day times 15 days of lost

⁹ The time horizon $T = 150$ is not chosen arbitrarily. Because COVID-19 emerged at different times across the U.S., we necessarily observe sample attrition at later “dates” of the analysis. These attrition rates are summarized in Appendix Fig. A1. We estimate the model through day 150 to ensure an adequate sample, but results are qualitatively unchanged if we expand the time horizon.

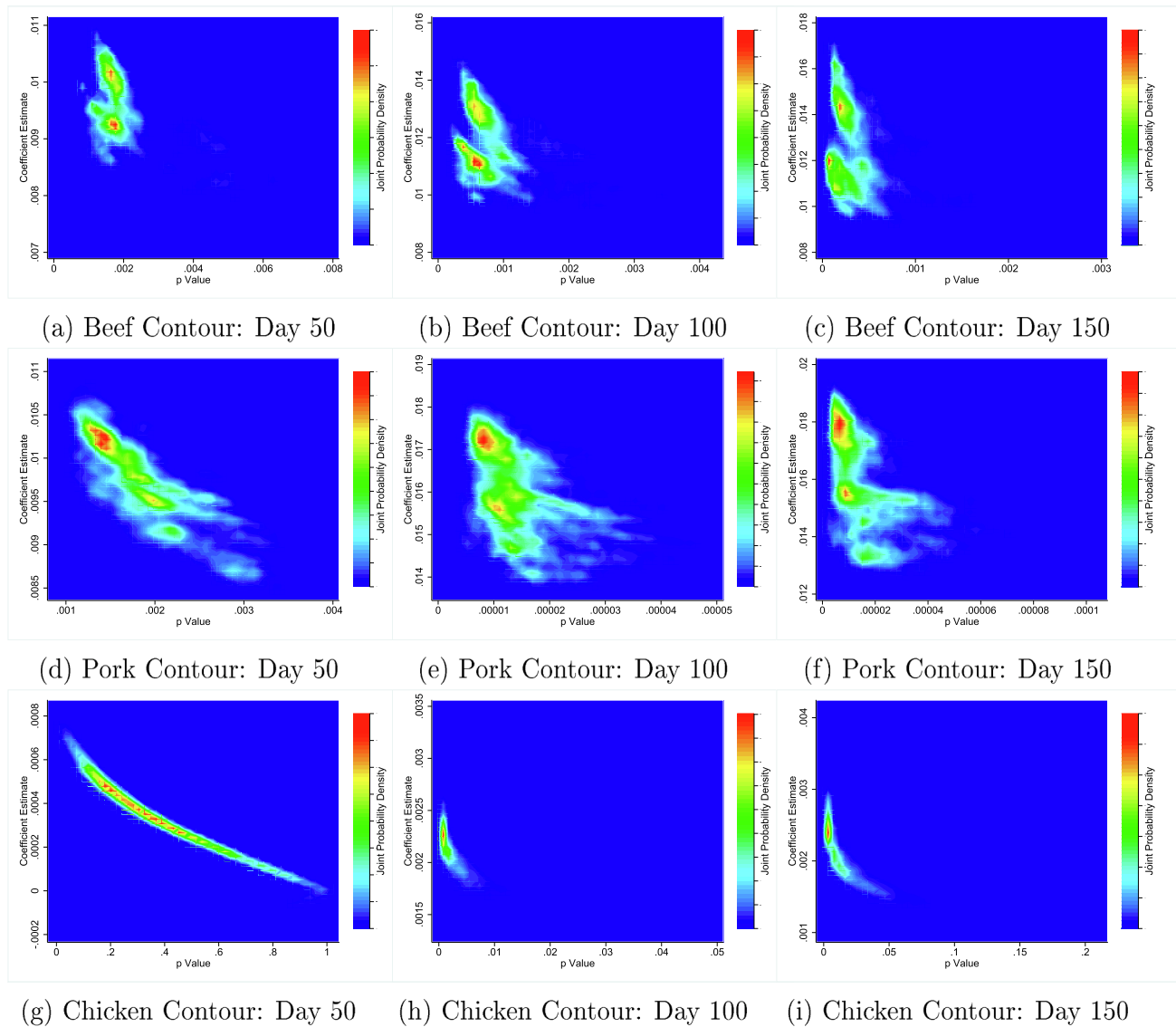


Fig. 4. Joint $(\hat{\beta}, p)$ Probability density estimates. **Notes:** These contour plots show the joint probability density estimates for $(\hat{\beta}, p)$ for days 50, 100, and 150. Density estimates for beef plants are shown in panels (a)–(c); density estimates for pork plants are shown in panels (d)–(f); and density estimates for chicken are shown in panels (g)–(i). The more concentrated the joint density (between the coefficient estimate and the statistical significance) the more intense the color; with orange and red hues indicating estimate “peaks,” where the majority of statistically significant point estimates occur.

wages.¹⁰ We calculate impacts on county-level morbidity by multiplying cases caused by the contemporaneous 7-day-moving-average U.S. case fatality rate (CFR), shown in Appendix Fig. A5. The economic costs of morbidity are \$14.05 multiplied by 8 h per day times 5 days per week times 52 weeks times 20 years. Nationwide impacts are assessed as the sum of county-level impacts.

¹⁰ Unfortunately, we do not have data on the occupation or wage rate of individuals who contracted or died from COVID-19. As such, we are not able to attribute specific wage rates to cases/fatalities. The U.S. Bureau of Labor Statistics reports hourly wage rates for meatpacking workers range from \$10.32/hour (10th percentile) to \$18.60/hour (90th percentile). However, many employees in this sector make less than the minimum wage (although this will not be reported as part of the government statistics). In order to better represent the distribution of wages earned by employees in this sector, we have used the median wage rate of \$14.05/hour reported by BLS in 2019. Note that this is only a partial estimate of infection. We exclude estimates of the costs to the health system of increased hospital visits and any potential reductions to long-term quality of life.

3.3. Meaningful correlates analysis

Finally, we perform a post-estimation analysis to assess the extent to which inclusion (or exclusion) of individual candidate correlates meaningfully affects our estimates of impact. To do so, we regress the point estimates $\hat{\beta}_t^i$ from our iterated regressions against two sets of indicators. The first set of indicators (t_t) take value one in time t and are equal to zero otherwise. These indicators measure the “average” estimate in a given period t . The second series of indicators (denoted t_c) are our variables of interest for the purposes of this analysis. These indicators take value one if a given candidate correlate (subscripted c) was included in the corresponding specification and are equal to zero otherwise. They measure the observed deviation from the average estimated impact in a given period t resulting from inclusion of candidate correlate c . This regression is formally specified as follows:

$$\hat{\beta}_t^i = \alpha + \sum_t \gamma_t t_t + \sum_c \theta_c t_c + \epsilon_t \quad (2)$$

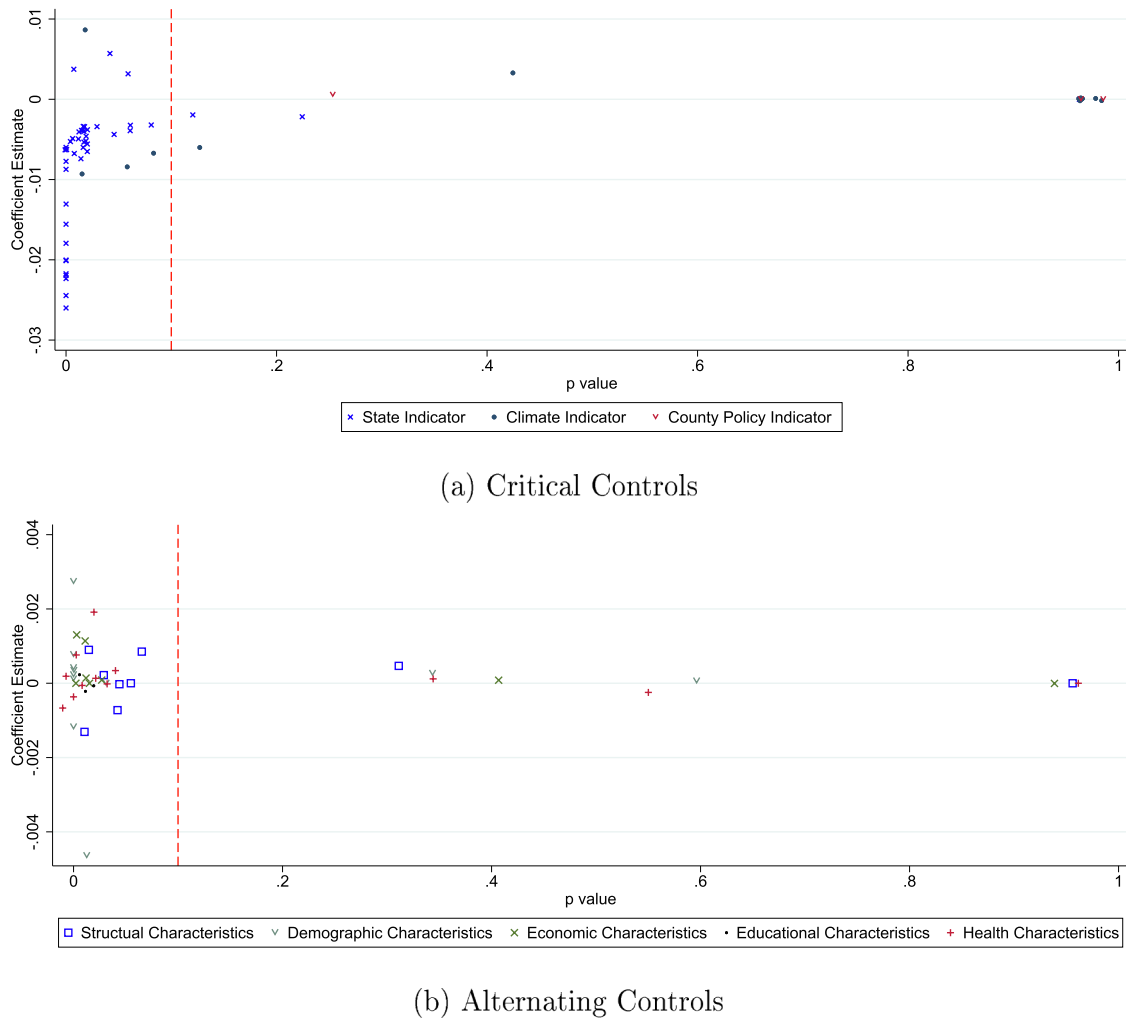


Fig. 5. Control variables. **Notes:** Panel (a) plots the topographic peak estimate for the critical controls (i.e., state indicators, climate indicators, and indicators for county-specific emergency, business closure, and stay-at-home policies), evaluated on day 150. Panel (b) plots the topographic peak for the 44 alternating controls (i.e., 9 structural, 11 demographic, 9 economic, 3 educational, and 12 health), also evaluated on day 150.

For coefficient $\hat{\beta}_i$, this model is run in a single regression with 9.36 million observations. We re-estimate for each $i \in \{\text{Beef}, \text{Pork}, \text{Chicken}\}$.

4. Results

After harmonizing county-level disease evolutionary stage and controlling for known and suspected drivers of transmission, we find that—150 days following the emergence of COVID-19 in a given county—the presence of a large beef packing facility increases the per capita infection rate by 110%, relative to comparable counties without meatpacking plants. Estimates indicate that large pork processing facilities and large chicken processing facilities increase per capita COVID-19 transmission rates by 160% and 20%, respectively. Following these initial transmission rate increases, daily per-capita case rates in meatpacking counties converge to (for beef and pork) or fall below (for chicken) rates observed in non-packing counties.

4.1. Iterated regression results

The contour plots in Fig. 4 show the joint probability density estimates for $(\hat{\beta}, p)$ for days 50, 100, and 150. Density estimates for beef plants are shown in panels (a)–(c); density estimates for pork plants are shown in panels (d)–(f); and density estimates for chicken are shown in

panels (g)–(i). Animated clips of the beef, pork, and chicken density estimates for each of the 150 days can be viewed by clicking on Appendix Fig. A2 in an Adobe Acrobat®PDF viewer. The box-and-whisker plots in Appendix Fig. A4 shows the distribution of the adjusted R-squared parameters for the iterated regressions.

From panels (a)–(c) of Fig. 4, the density estimates for the impacts of beef processing plants we see the range of specifications converge over time—both with respect to the measure of statistical precision and the magnitude of the coefficient estimate.¹¹ For example, 50 days following the first confirmed COVID-19 case, the standard deviation of the p-value estimates is 0.0020. By day 100, the standard deviation in p-value estimates falls to 0.0012, and by day 150, this standard deviation falls to

¹¹ The reader may note the “two islands” in the density estimates for beef and to a certain extent pork in Fig. 4. This is a result of running a multitude of model specifications. For panels (b) and (e) of the figure, the predominant peak of the density plots for both beef and pork come from models which include “% of Household, Non-English”, “% Born in MX”, and “% Hispanic” as demographic controls. The islands in the density plots lying away from the predominant are a grouping of coefficient results associated with model specifications that do not control for these demographic factors. In panels (c) and (f), the two islands in the density plots are differentiated by models that include a control for “% of adults w/o HS diploma or GED”, and those which do not.

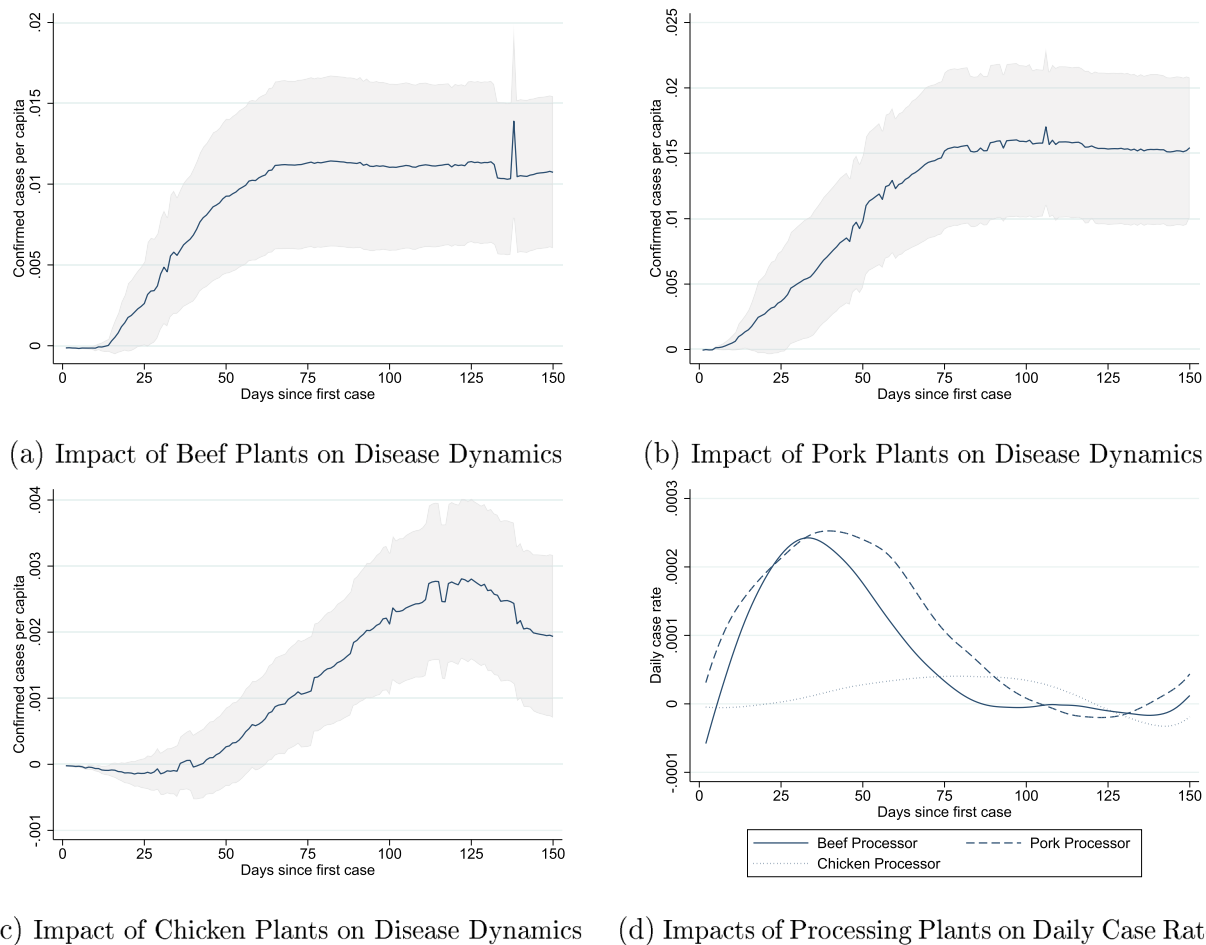


Fig. 6. Processing plants and COVID-19 transmission. **Notes:** Panels (a)–(c) plot the non-parametric impacts of beef, pork, and chicken processing plants on county-level disease dynamics. Panel (d) shows the daily per capita case rates implied by the estimates in panels (a)–(c).

0.0008. Further, the range of coefficient estimates increases in magnitude over time. The mean impact estimate for the presence of beef processing plants is 0.009 cases per capita 50 days following the first confirmed case, rising to 0.012 cases per capita by day 100, and 0.013 cases per capita by day 150.

A similar pattern is observed for pork processing plants (panels (d)–(f) of Fig. 4). The standard deviation in p-value estimates falls from 0.009 as of 50 days following the first confirmed case, to 0.000031 as of day 150. Mean coefficient estimates increase from 0.0098 on day 50, to 0.016 cases per capita on day 100, to 0.016 cases per capita by day 150. In contrast, for chicken processing plants (panels (g)–(i) of Fig. 4), statistical precision and the range of coefficient estimates do not appear to converge until later in the evolution of the outbreak. The standard deviation in p-values for chicken processing plants falls from 0.304 on day 50 to 0.013 on day 100, then increases to 0.06 on day 150. The mean impact estimate for the presence of chicken processing plants is 0.0003 cases per capita 50 days following the first confirmed case, rising to 0.0024 cases per capita by day 100, and 0.0026 cases per capita by day 150.

Fig. 5 summarizes the performance of control variables. Panel (a) plots the topographic peak estimate for the critical controls (i.e., state indicators, climate indicators, and indicators for county-specific emergency, business closure, and stay-at-home policies), evaluated on day 150 (see Methodology Section 3, Table 1). Panel (b) plots the topographic peak for the 44 alternating controls (i.e., 9 structural, 11

demographic, 9 economic, 3 educational, and 12 health), also evaluated on day 150. These topographic peaks are the “most likely” coefficient estimate on these controls as chosen by the peak of the joint probability distribution across coefficient estimates and p-values for all models that include this control.

Fig. 5, panel (a) shows 39 of the 45 state-specific indicator variables are statistically significant at 95%. Of those, Florida and Louisiana were largest in magnitude at 0.006 and 0.004, respectively. Of the county-specific policy indicators, none of the three indicators were statistically significant (at 90%). Given the majority of policy actions occurred at the state level (as opposed to the county level), it is expected that these impacts are estimated imprecisely. Additionally, in panel (a) of Fig. 5, four of the 16 climate indicators are statistically significant at 90%.

Coefficient estimates for the alternating controls are displayed in panel (b) of Fig. 5. Coefficient estimates for seven of the nine structural characteristic variables are statistically significant. Nine of the 11 demographic variables are statistically significant. The percent of GOP voters and percent of population age 65 and older are associated with lower levels of disease incidence. All other demographic indicators are positively correlated with disease incidence. Six of eight economic variables are statistically significant with unemployment rate having the largest positive correlation with disease incidence. All education variables are statistically significant and of the expected sign. The percentage of the population with less than high school education is positively

correlated with disease incidence. The percentage of the population with some college or a college degree is negatively correlated with disease incidence. Eight of the 12 health indicators are statistically significant, all of which are of the expected sign.

4.2. Dynamic impact estimates

Fig. 6 plots the non-parametric impacts of beef (panel a), pork (panel b), and chicken (panel c) processing plants on county-level disease dynamics. In each panel of Fig. 6, the topographic peak for day 1 resides at the origin. For both beef, pork, and chicken plants, the day 1 point estimates are -0.00013 , -0.00005 , and -0.00002 , respectively. This suggests that—at the outset of a county-level outbreak—the presence of a meat processing plant does not have a detectable impact on case rates.

In panels (a) and (b) of Fig. 6, county-level impacts for beef and pork facilities—as defined by the topographic peak procedure (see Methodology Section 3.1)—increase up to day 60 and then remain relatively flat thereafter.¹² The impact of beef processing facilities becomes statistically significant (at 90% confidence) on day 28 and remains statistically significant over the remainder of the sample time horizon. Similarly, the impact of pork processing facilities becomes statistically significant (at 90%) on day 27. By day 150, infection rates in beef- and pork- packing counties, respectively, are 0.0107 and 0.0154 cases per capita (statistically significant at 95%) higher, relative to comparable counties without a packing plant. This equates to approximately 650 additional infections in the median-populace beef-packing county and an additional 563 cases in the median-populace pork-packing plant. For context, at the same point in the outbreak (i.e., day 150), the median no-packing-plant county had an observed per capita case rate of 0.0097. Thus, the estimated beef- and pork- packing impacts equate to 110% and 160% increases, relative to this no-plant-county infection rate.

Panel (c) of Fig. 6 shows infection rates in counties with chicken processing facilities remain statistically indistinguishable from counties without processing plants until day 63. However, by day 150, chicken plants have generated an additional 0.0019 cases per capita (statistically significant at 99%), relative to comparable counties without packing plants. For the median population chicken processing county, this equates to an additional 103 cases, and represents a 20% increase in case rates relative to the median population no-plant county. Most poultry processing operations are substantially more automated and mechanized at the first stage of processing (i.e., harvest), when compared to beef and pork processing facilities. As such, these operations are likely to be more resilient to disease outbreaks among employees and are well suited for socially distanced work and maintaining throughput with a limited human workforce. This is consistent lower per-capita confirmed cases observed in counties with chicken processing plants.

Panel (d) of Fig. 6 shows the daily per capita case rates implied by the estimates in panels (a)–(c). These estimates are smoothed using a locally weighted regression with a 0.4 bandwidth of centered subsets of observations for calculating smoothed values (Cleveland, 1979). Referring to panel (d), we see that daily per-capita case rates in meatpacking counties have now converged to (for beef and pork) or fallen below (for chicken) rates in non-packing counties. This suggests cases are no longer expanding in beef and pork packing counties relative to non-packing counties. Additionally, daily case rates in broiler are growing slower than in non-packing counties.

The convergence in daily case rates in meatpacking and non-meatpacking counties is likely driven by a combination of three factors. First, the industry took numerous steps to reduce transmission in

packing facilities. These steps included imposition of social distancing requirements, establishing physical barriers between workers, improved use of PPE, updated ventilation systems, and installation of ultraviolet lights.¹³ The second factor relates to the evolving nature of the pandemic over time. Early in the pandemic, daily infections were driven primarily by semi-isolated outbreak clusters. Meatpacking plants proved to be a hotbed of these outbreak clusters. For example, the widely publicized outbreak in the Smithfield pork processing facility in Sioux City, South Dakota led to more than 600 cases (Lussenhop, 2020). However, as the disease became more widely prevalent in the U.S. in late summer and early fall, daily infections were driven by community spread rather than isolated outbreak clusters. Appendix Fig. A3 plots the daily average case rates for non-packing counties implied by our model. The Figure provides evidence of the growing importance of community spread relative to outbreak clusters, as case rates in non-packing counties began to rise at this time. As community spread became more prevalent, the importance of any one transmission environment was diminished. Finally, because case rates were higher earlier on in meatpacking counties, a portion of infected individuals likely acquired at least temporary immunity to the disease. As workers became immune, packing plants became a less important location for spread. Additionally, this immunity may also have slowed community spread in packing plant counties through partial herd immunity. We are unable to separate the effects of these three factors with our analysis.

4.3. Meaningful correlates results

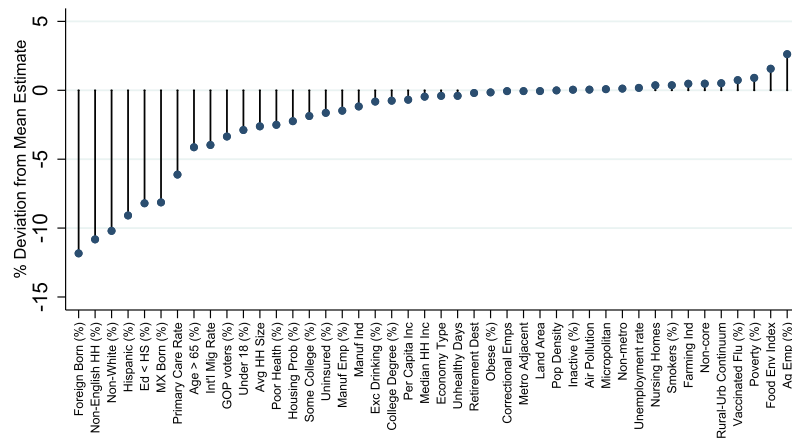
Fig. 7 summarizes the results of the meaningful correlates analysis.¹⁴ The vertical bars in panels (a), (b), and (c) of Fig. 7 represent the percent deviation in the impact estimate associated with the 43 candidate correlates included in the iterated regressions. These deviations are evaluated relative to the mean day-150 estimate.

Referring to panel (a) of Fig. 7, we see that our estimate of the beef impact is most sensitive to the inclusion of demographic variables Foreign Born (%), Non-English Households (%), Non-White (%). Variables Foreign Born (%), Non-English Households (HH) (%), and Non-White (%) are associated with a 12%, 11%, and 10% reduction, respectively, in the impact estimate (relative to the mean). Post-estimation sensitivity results are similar for pork impact estimates in panel (b) of Fig. 7. Foreign Born (%), Non-English HH (%), and Non-White (%) are again the candidate correlates with the largest effect on our measure of the day-150 impacts of pork facilities. Inclusion of these variables reduces the impact estimate for pork by 11%, 9%, and 7%, respectively. Given the disproportionate impact among minority workers—56% of meatpacking workers testing positive were Hispanic, 19%

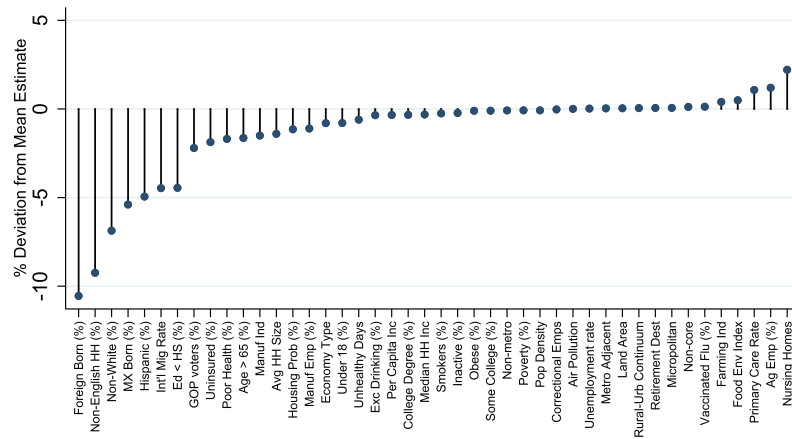
¹³ Ideally, one could account for these factors by including information on the corporate ownership of the facility in a given packing plant county. However, because we have separated out effects for beef versus pork versus broiler processing facilities, we are unable to fully control for individual corporate entities. Instead, we re-estimate Eq. (1), including three additional indicator variables, which take value one if the county includes one of the top-4 beef processors (Cargill, JBS/Smithfield, National, Tyson), one of the top-4 pork processors (JBS/Smithfield/Cargill, IBP/Tyson, Swift (Conagra), Seaboard), or one of the top-4 broiler processors (Tyson, Pilgrims, Sanderson, Perdue). These indicators are interpreted additively with the original beef, pork, and broiler processor indicators. Non-parametric estimates of COVID-19 transmission dynamics in counties with facilities owned by one of the top-4 processors versus counties with facilities owned by “other” processors are plotted in Appendix Fig. A7. The results suggest that—while cases in top-4 beef and pork packing counties increased substantially over other packing counties, the rates in these top-4 counties fell in later periods both relative to other packing counties and non-packing counties. In contrast, case rates in top-4 broiler processor counties are increasing relative to other broiler processor counties and non-processing counties.

¹⁴ Raw coefficients from estimating Eq. (2) are shown in Appendix Table A2.

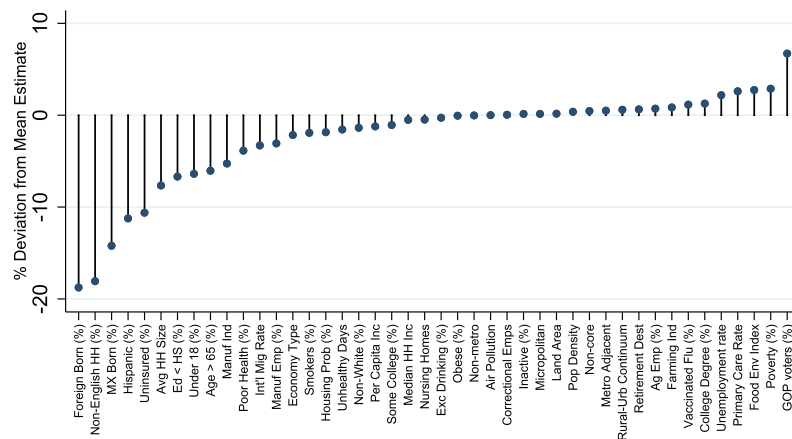
¹² In panel (a) of Fig. 6, the spike in at day 138 is related to the issue of the two islands addressed above in footnote 10. At day 138, the grouping of coefficient estimates associated with controlling for “% Employed Agriculture” briefly dominates the grouping that controls for “% Foreign Born”, “% Hispanic”, “Int'l Migration Rate”, and “% of adults w/o HS diploma or GED”.



(a) Impact on Beef Estimate



(b) Impact on Pork Estimate



(c) Impact on Chicken Estimate

Fig. 7. Contributory factors analysis. **Notes:** The vertical bars in panels (a), (b), and (c) represent the percent deviation in the impact estimate associated with the 43 candidate correlates included in the iterated regressions. These deviations are evaluated relative to the mean day-150 estimate.

Table 2
Mortality and morbidity costs from meatpacking plants.

Variable	Units	Impact Estimate
Disease Incidence		
Infections Caused		
Beef Plants	1,000 cases	110.33
Pork Plants	1,000 cases	199.54
Chicken Plants	1,000 cases	23.80
Total	1,000 cases	333.67
Deaths Caused		
Beef Plants	1,000 deaths	6.07
Pork Plants	1,000 deaths	10.72
Chicken Plants	1,000 deaths	1.35
Total	1,000 deaths	18.14
Economic Impacts		
Lost Wages-Productivity		
Beef Plants	\$ Million	186.00
Pork Plants	\$ Million	336.43
Chicken Plants	\$ Million	40.13
Total	\$ Million	562.57
Morbidity Costs		
Beef Plants	\$ Million	3,548.33
Pork Plants	\$ Million	6,263.04
Chicken Plants	\$ Million	791.02
Total	\$ Million	10,602.40
Total Economic Cost	\$ Million	11,164.98

were black, and 13% were Asian (Waltenburg et al., 2020)—failing to account for these demographic factors creates an upward bias in transmission estimates.

Meaningful correlates are also similar for estimated chicken plant impacts. As with beef and pork plants, variables Foreign Born (%) and Non-English HH (%) have the largest effect on the impact estimate. However, these effects appear much larger in magnitude for chicken plants than for beef and pork. Inclusion of Foreign Born (%) and Non-English HH (%) each reduce the chicken impact by approximately 18%. These findings—for beef, pork, and chicken—are further confirmation that ethnic minorities, that comprise the majority of the meatpacking workforce are disproportionately affected by COVID-19.

4.4. Mortality and morbidity costs

Table 2 summarizes the aggregate mortality and morbidity costs attributed to meatpacking-plant-induced COVID-19 transmission and infection. These estimates are not intended to capture the macro economic costs associated with the COVID-19 pandemic or the associated multiplier effects suffered by host communities. As such, the government, state-level, and plant-level stimulus measures implemented are irrelevant to the analysis. The per capita impacts (Fig. 6) suggest that large packing plants have generated 334 thousand COVID-19 cases in the United States (through the end of October 2020). Approximately 33% of these infections were generated by large beef packing facilities and 60% were caused by pork processing facilities. Broiler chicken facilities account for 7% of packing-plant-related infections.

Multiplying the case rates in Table 2 by the contemporaneous 7-day-moving-average case fatality rate (CFR) suggests that packing plants have generated over 18 thousand COVID-19-related deaths. Beef and pork facilities combine for about 93% of these deaths with 6.1 thousand and 10.7 thousand, respectively. Taken together, our estimates suggest that the COVID-19 mortality and morbidity associated with large packing plants have generated nearly \$11.2 billion in economic costs to the U.S. economy.¹⁵

¹⁵ The reported hourly wage rates for meatpacking workers range from \$10.32/hour (10th percentile) to \$18.60/hour (90th percentile). Using these bounds provides a range of total economic costs from \$ 8.2 billion to \$14.8 billion.

5. Discussion

This paper uses a topographic regression procedure to investigate the extent to which the presence of a large meatpacking plant has affected county-level disease transmission dynamics. We find that—within 60 days after emergence of COVID-19 in a given county—the presence of a large beef (pork) packing facility increases per capita infection rates by 110% (160%), relative to comparable counties without packing plants. This translates to 334 thousand COVID-19 cases across the United States attributable to large meatpacking operations. This estimate encompasses both direct infections to meatpacking workers as well as community spread outside the operations but attributable to those facilities.

Our estimates suggest that previous reports significantly understate the impact of meatpacking facilities on COVID-19 case rates. Yet, our estimated infection rates are likely conservative for a number of reasons. First, our model specification does not take into account COVID-19 case rate “leakages;” i.e., only those COVID-19 cases recorded within the county where a plant is located can be attributable to the meatpacking sector. As such, any meatpacking-related COVID-19 transmission that occurs outside the county boundary is not attributable to a meatpacking facility. As an example, if a meatpacking plant employee contracted COVID-19 at work but traveled outside the county (e.g., for housing, shopping, medical care) spreads the disease, those cases generated by worker mobility would not be attributed to the packing plant. Further, cases emanating from meatpacking plants that are being counted in neighboring counties also work to make our estimated impacts conservative as they elevate the case rates observed in our “baseline” or “control” counties. Finally, we only consider large meatpacking plants, as defined by the Food Safety and Inspection Service, and thereby fail to quantify the possible cases attributable to small- and medium-size meat processing operations.

The racial and ethnic disparities in COVID-related health impacts, and the associated economic consequences, observed in the United States are an additional cause for the heightened concern surrounding meatpacking industry impacts. As COVID cases increased in plants, processors began to blame the workforce (largely Latino, Asian, and Black) for bringing the virus to the workplace (Iles and Montenegro de Wit, 2020). It is not so far fetched to believe that outbreaks at these facilities are likely to exacerbate preexisting racial marginalization and stigma (Peters, 2020). Further, traditional interventions geared toward mitigating harm related to COVID-19 (e.g., economic stimulus) are unlikely to be effective or adequate at addressing racial disparity issues.

In aggregate, we estimate that the COVID-19 mortality and morbidity associated with large packing plants has generated more than \$11.6 billion in economic costs to the rural economy with beef and pork facilities combined accounting for the preponderance (93%) of these costs. COVID-19-related cost estimates reported herein likely dramatically understate the true economic losses incurred and can be considered a lower-bound estimate. For infected people who do not die, we do not account for the potential long-term costs associated with COVID-19-related illnesses, including chronic health-related issues and quality-of-life reductions. Further, we do not account for the costs associated with medical treatment or the investments made by processors to augment the work environment in an attempt to safeguard worker health. Quantifying the costs associated with these additional aspects of the COVID-19 pandemic, as it pertains to the meatpacking segment of the food supply chain, would present itself as an avenue for future research in this area.

The increased COVID-19 transmission rates—coupled with long-standing concerns over the horizontally concentrated and vertically integrated structure of the industry—have prompted critics to question in the fundamental resiliency of the industrial meatpacking system. Many critical of this system have advocated for a smaller and more geographically dispersed industry (e.g., Taylor et al. (2020)), suggesting that this would make the meatpacking industry less susceptible to shutdowns and massive disruptions like those experienced during the

early parts of the pandemic in 2020. While the infection rates and COVID-19 mortality costs associated with the meatpacking industry are substantial, those critical of the industry's structure must recognize that sacrificing the scale, concentration, and efficiency of the industry we know today, in the name of disease-transmission resiliency, would come at a significant cost. A smaller scale, more geographically dispersed industry would come at a price; namely adding costs back into a sector that has evolved to eliminate them. Our results, suggesting that the poultry segment of the meat supply chain was more resilient to the COVID-19 pandemic, suggests that automation and technological innovation would be a more promising way to improving supply chain resiliency while preserving or enhancing efficiency.

CRediT authorship contribution statement

Tina Saitone: Conceptualization, Writing - original draft, Writing - review & editing. **K. Aleks Schaefer:** Conceptualization, Validation, Visualization, Writing - original draft, Writing - review & editing, Methodology, Data curation. **Daniel P. Scheitrum:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing.

Appendix A

See [Figs. A1, A2, A3, A4, A5, A6 and A7](#), [Tables A1 and A2](#).

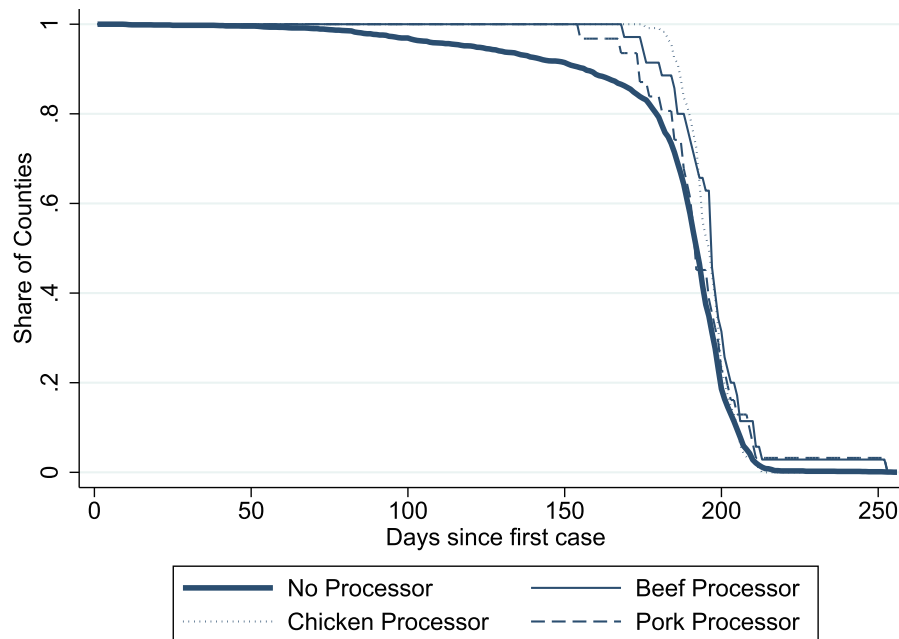


Fig. A1. Sample time horizon and county attrition.

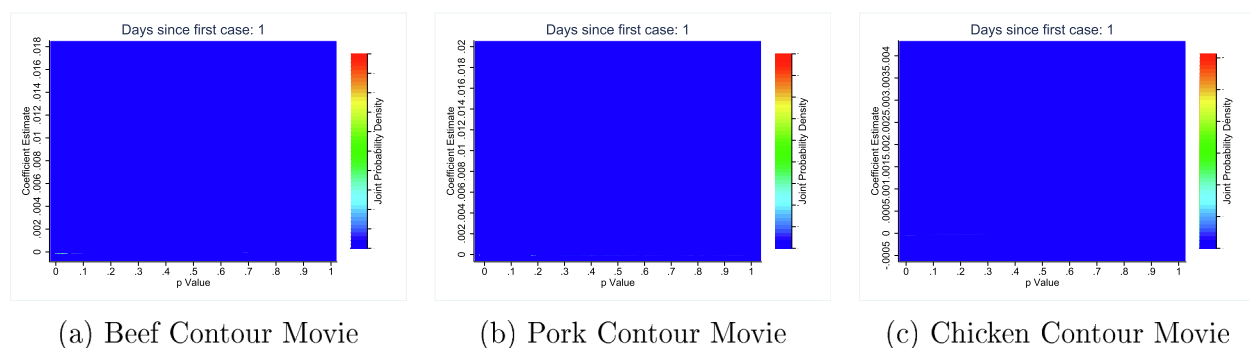


Fig. A2. Processing plants and COVID-19 transmission. **Notes:** Panels (a)–(c) show animated clips of the beef, pork, and chicken density estimates for each of the 150 days. These can be viewed by clicking on the images in an Adobe Acrobat®PDF viewer. The more concentrated the joint density (between the coefficient estimate and the statistical significance) the more intense the color; with orange and red hues indicating estimate “peaks”, where the majority of statistically significant point estimates occur.

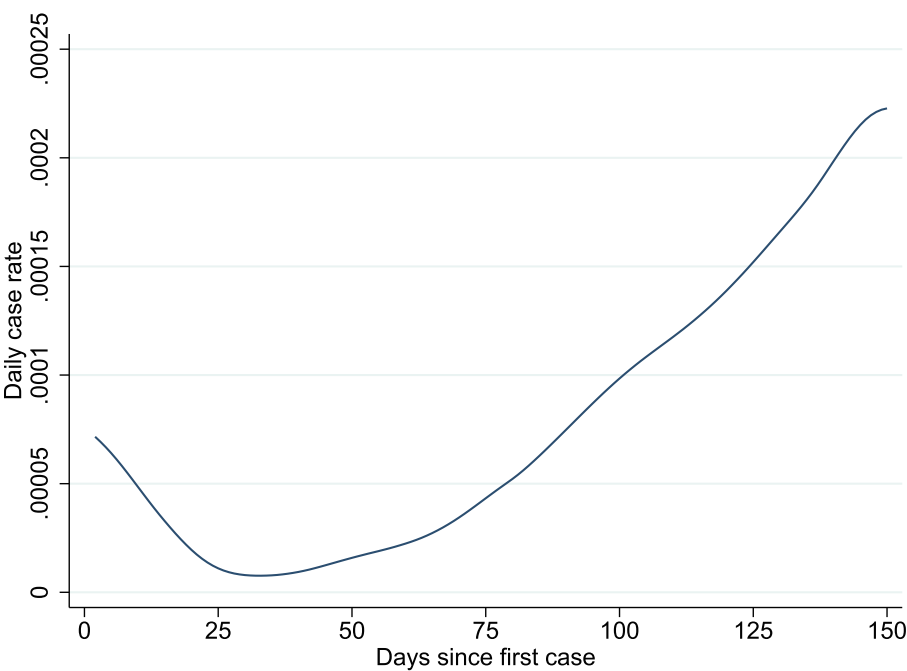


Fig. A3. Mean daily per capita case rate in non-meatpacking counties. **Notes:** This figure plots the non-parametric impacts of of daily per capita case rates in non-packing counties. These estimates are smoothed using a locally weighted regression with a 0.4 bandwidth of centered subsets of observations for calculating smoothed values (Cleveland, 1979).

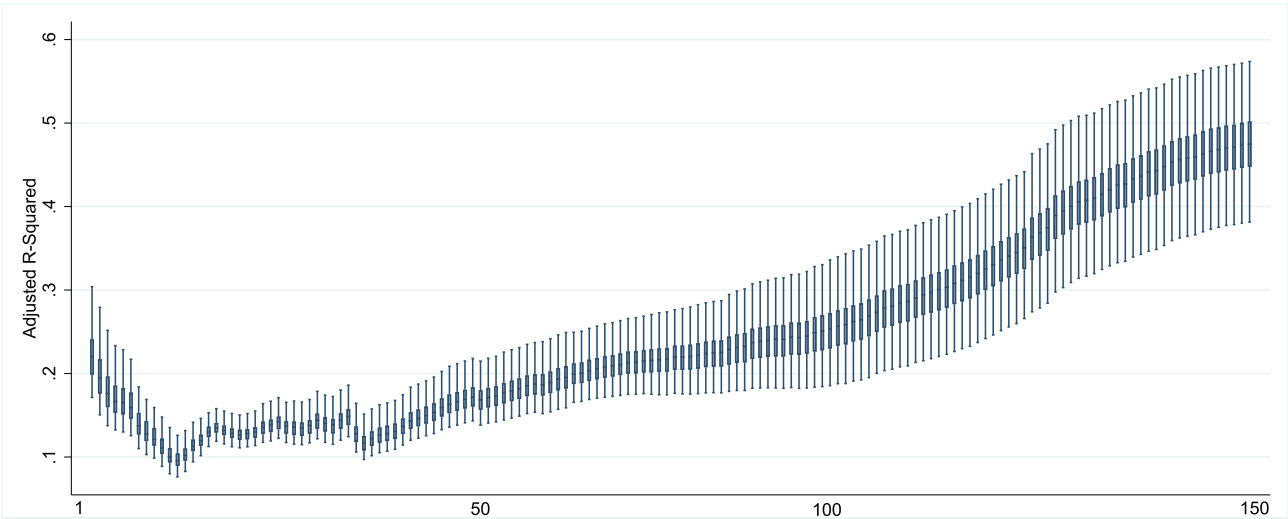


Fig. A4. Model performance. **Notes:** These box-and-whisker plots show the distribution of the adjusted R-squared parameters for the iterated regressions.

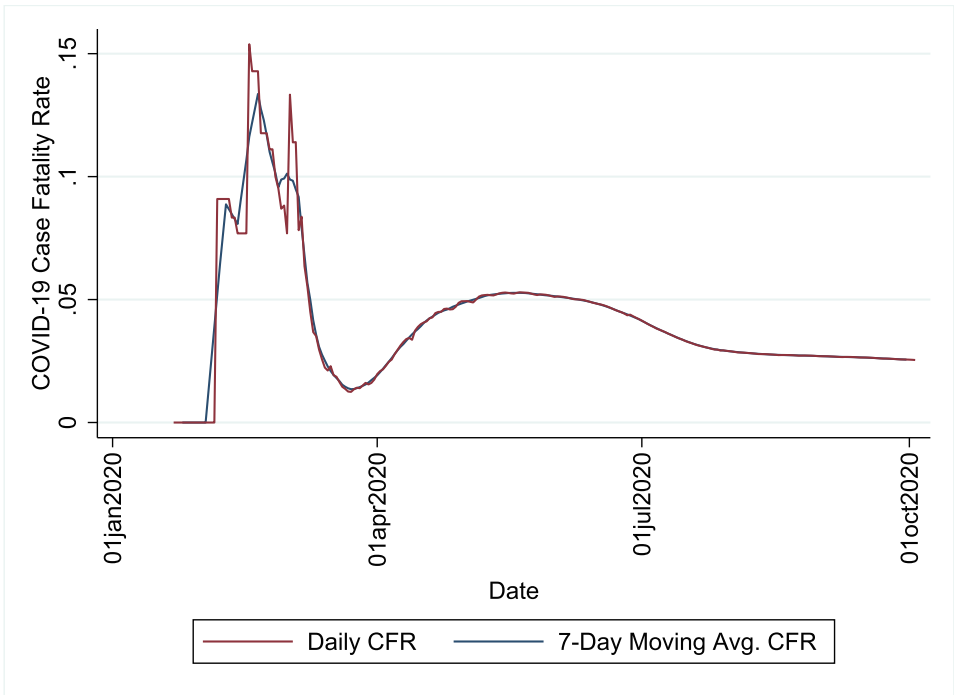


Fig. A5. COVID-19 Case Fatality Rate (CFR) Over Time. **Notes:** Figure plots daily and 7-day-moving-average CFR for COVID-19, constructed using data from [USAFacts \(2020\)](#).

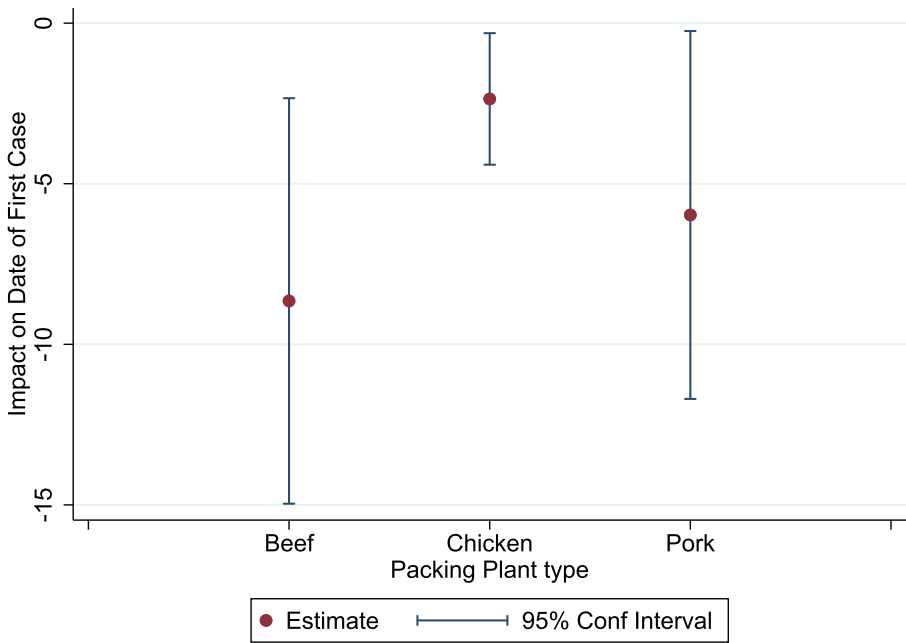
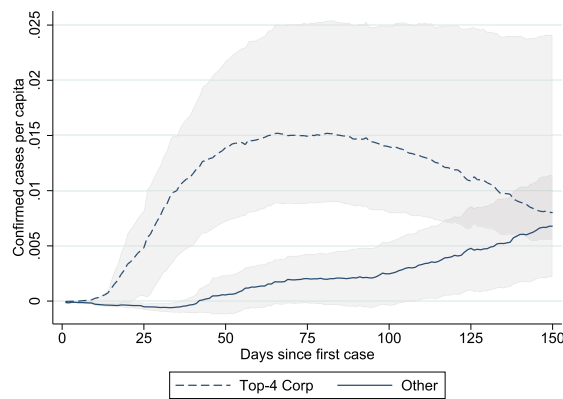
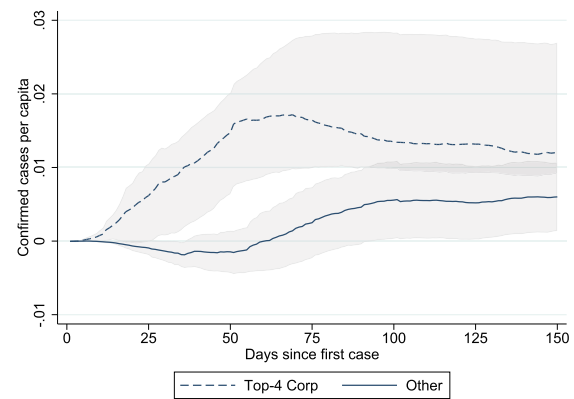


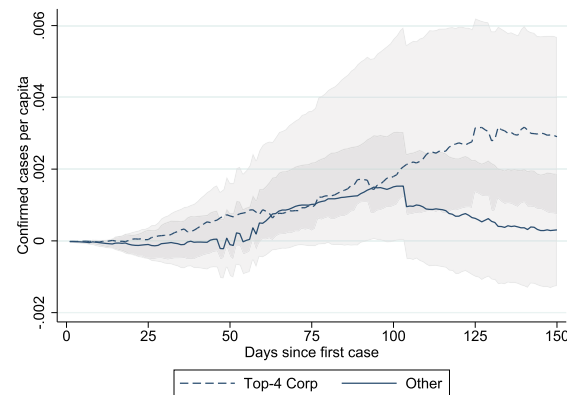
Fig. A6. Arrival of COVID-19 in meatpacking counties. **Notes:** Figure shows the impacts of meatpacking plants on the date of the first COVID-19 case in the county. Reported results are the topographic peaks from our iterated regression procedure.



(a) Impact of Beef Plants on Disease Dynamics



(b) Impact of Pork Plants on Disease Dynamics



(c) Impact of Chicken Plants on Disease Dynamics

Fig. A7. Top-4 versus other processing plants and COVID-19 transmission. **Notes:** Panels (a)–(c) plot the non-parametric impacts of top-4 and “other” beef, pork, and chicken processing plants on county-level disease dynamics.

Table A1

Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Dependent Variable					
Cases Per Capita	445,224	0.0049	0.0083	0	0.1437
Meat Processor Indicators					
Beef Plant	445,224	0.0118	0.1079	0	1
Pork Plant	445,224	0.0104	0.1017	0	1
Chicken Plant	445,224	0.0391	0.1938	0	1
Structural Characteristics					
Nursing Homes	445,224	5.87	17	0	667
Correctional Emps	445,224	45.79	293	0	7,121
Land Area	445,224	954.1	1,314	22.83	20,057
Rural-Urb Continuum	445,224	4.96	3	1	9
Non-metro	445,224	0.63	0	0	1
Micropolitan	445,224	0.21	0	0	1
Retirement Dest	445,224	0.14	0	0	1
Non-core	445,224	0.42	0	0	1
Metro Adjacent	445,224	0.34	0.47	0	1
Demographic Characteristics					
Int'l Mig Rate	445,224	0.82	1	−0.91	16.31
Pop Density	445,224	201.78	1,440	0.26	69,468
Under 18 (%)	445,224	23.48	3	9.11	40.13
Age >65 (%)	445,224	15.87	4	3.73	43.38
Hispanic (%)	445,224	8.31	13	0	95.74
Foreign Born (%)	445,224	4.59	5.47	0	53.25
MX Born (%)	445,224	1.96	4	0	39.51
Avg Household Size	445,224	2.52	0	1.82	4.97
Non-White (%)	445,224	78.68	19	2.8	99.16
GOP voters (%)	445,074	0.64	0	0.08	0.95
Non-English Household (%)	445,224	1.81	3	0	44.02

(continued on next page)

Table A1 (continued)

Variable	Obs	Mean	Std. Dev.	Min	Max
Economic Characteristics					
Unemployment rate	445,224	4.12	1.4	1.3	18.1
Median Household Inc	445,224	52,554	13,641	25,385	140,382
Per Capita Inc	445,074	26,852	6,332	10,148	72,832
Poverty (%)	445,224	15.21	6	2.6	54
Ag Emp (%)	445,074	4.84	6	0	54.86
Manuf Emp (%)	445,074	12.58	7	0	48.02
Farming Ind	445,224	0.13	0.34	0	1
Manuf Ind	445,224	0.17	0	0	1
Education Characteristics					
Ed < HS (%)	445,224	13.54	6	1.41	66.34
Some College (%)	445,224	21.76	4	4.12	37.05
College Degree (%)	445,224	21.33	9	5.38	74.56
Health Characteristics					
Poor Health (%)	445,224	18.02	5	8	41
Unhealthy Days	445,224	4.01	0.7	2.4	6.6
Smokers (%)	445,224	17.52	4	6	41
Obese (%)	445,224	33.04	5	12	58
Food Env Index	442,721	7.48	1	0	10
Inactive (%)	445,224	27.55	6	10	50
Exc Drinking (%)	445,224	17.46	3	8	29
Uninsured (%)	445,224	11.41	5.1	2	34
Primary Care Rate	425,473	53.75	33	0	514
Vaccinated Flu (%)	445,074	41.93	10	5	66
Air Pollution	445,224	9.09	2	3	19.7
Housing Prob (%)	445,224	13.68	4	3	45

Table A2

Post-estimation regressions.

VARIABLES	(1) Beef	(2) Pork	(3) Chicken
Structural Characteristics			
Nursing Homes	4.99e-05*** (8.84e-07)	0.000371*** (7.73e-07)	-1.25e-05*** (2.93e-07)
Correctional Emps	-8.28e-06*** (8.81e-07)	-4.28e-06*** (7.71e-07)	1.31e-06*** (2.90e-07)
Land Area	-7.66e-06*** (8.84e-07)	6.75e-06*** (7.75e-07)	4.37e-06*** (2.90e-07)
Rural-Urb Continuum	7.06e-05*** (8.95e-07)	8.49e-06*** (7.74e-07)	1.56e-05*** (2.92e-07)
Non-metro	1.70e-05*** (8.91e-07)	-1.38e-05*** (7.70e-07)	-6.12e-07** (2.89e-07)
Micropolitan	1.13e-05*** (8.81e-07)	1.06e-05*** (7.69e-07)	3.73e-06*** (2.88e-07)
Retirement Dest	-2.68e-05*** (8.74e-07)	9.77e-06*** (7.68e-07)	1.67e-05*** (2.88e-07)
Non-core	6.61e-05*** (8.95e-07)	1.99e-05*** (7.77e-07)	1.20e-05*** (2.91e-07)
Metro Adjacent	-8.03e-06*** (8.87e-07)	5.66e-06*** (7.74e-07)	1.30e-05*** (2.90e-07)
Demographic Characteristics			
Int'l Mig Rate	-0.000545*** (1.13e-06)	-0.000748*** (8.53e-07)	-8.62e-05*** (3.07e-07)
Pop Density	-9.52e-07 (1.30e-06)	-1.27e-05*** (1.02e-06)	9.83e-06*** (3.39e-07)
Under 18 (%)	-0.000396*** (1.08e-06)	-0.000133*** (9.25e-07)	-0.000167*** (2.74e-07)
Age >65 (%)	-0.000567*** (1.08e-06)	-0.000274*** (8.87e-07)	-0.000158*** (2.94e-07)
Hispanic (%)	-0.00125*** (1.13e-06)	-0.000828*** (8.11e-07)	-0.000294*** (2.93e-07)
Foreign Born (%)	-0.00162*** (1.16e-06)	-0.00177*** (1.11e-06)	-0.000491*** (3.43e-07)
MX Born (%)	-0.00112*** (1.06e-06)	-0.000903*** (8.30e-07)	-0.000372*** (3.27e-07)
Avg Household Size	-0.000359*** (1.10e-06)	-0.000235*** (8.79e-07)	-0.000200*** (2.70e-07)
Non-White (%)	-0.00140*** (1.11e-06)	-0.00115*** (8.82e-07)	-3.58e-05*** (2.98e-07)
GOP Voters (%)	-0.000460*** (1.14e-06)	-0.000369*** (8.99e-07)	0.000176*** (4.38e-07)

(continued on next page)

Table A2 (continued)

VARIABLES	(1) Beef	(2) Pork	(3) Chicken
Non-English Household (%)	−0.00148*** (1.19e-06)	−0.00155*** (1.12e-06)	−0.000473*** (3.72e-07)
Economic Characteristics			
Unemployment Rate	2.41e-05*** (8.90e-07)	3.74e-06*** (7.76e-07)	5.72e-05*** (3.12e-07)
Median Household Inc	−6.35e-05*** (8.94e-07)	−5.23e-05*** (7.78e-07)	−1.32e-05*** (2.90e-07)
Per Capita Inc	−9.38e-05*** (8.68e-07)	−5.67e-05*** (7.68e-07)	−3.19e-05*** (2.84e-07)
Poverty (%)	0.000124*** (8.61e-07)	−1.28e-05*** (7.46e-07)	7.56e-05*** (2.83e-07)
Ag Emp (%)	0.000360*** (9.26e-07)	0.000201*** (7.94e-07)	1.88e-05*** (2.86e-07)
Manuf Emp (%)	−0.000203*** (8.86e-07)	−0.000185*** (7.75e-07)	−8.04e-05*** (2.86e-07)
Economy Type	−5.53e-05*** (8.89e-07)	−0.000134*** (7.75e-07)	−5.65e-05*** (2.83e-07)
Farming Ind	6.55e-05*** (8.99e-07)	6.68e-05*** (7.92e-07)	2.23e-05*** (2.94e-07)
Manuf Ind	−0.000161*** (8.83e-07)	−0.000251*** (7.73e-07)	−0.000138*** (2.87e-07)
Educational Characteristics			
Ed < HS (%)	−0.00113*** (6.07e-07)	−0.000746*** (5.02e-07)	−0.000175*** (1.81e-07)
Some College (%)	−0.000256*** (5.26e-07)	−1.60e-05*** (4.74e-07)	−2.80e-05*** (1.81e-07)
College Degree (%)	−0.000103*** (5.81e-07)	−5.51e-05*** (5.04e-07)	3.32e-05*** (1.99e-07)
Health Characteristics			
Poor Health (%)	−0.000344*** (9.38e-07)	−0.000283*** (8.35e-07)	−0.000101*** (3.04e-07)
Unhealthy Days (%)	−5.50e-05*** (9.84e-07)	−0.000101*** (8.74e-07)	−4.07e-05*** (3.16e-07)
Smokers (%)	5.04e-05*** (1.05e-06)	−4.16e-05*** (9.20e-07)	−5.04e-05*** (3.33e-07)
Obese (%)	−2.08e-05*** (1.03e-06)	−1.70e-05*** (9.18e-07)	−1.37e-06*** (3.30e-07)
Food Env Index	0.000215*** (1.08e-06)	8.27e-05*** (9.42e-07)	7.18e-05*** (3.35e-07)
Inactive (%)	5.73e-06*** (1.05e-06)	−3.75e-05*** (9.11e-07)	3.68e-06*** (3.33e-07)
Exc Drinking (%)	−0.000112*** (1.01e-06)	−5.89e-05*** (8.95e-07)	−7.17e-06*** (3.27e-07)
Uninsured (%)	−0.000224*** (9.48e-07)	−0.000313*** (8.44e-07)	−0.000278*** (3.67e-07)
Primary Care Rate	−0.000839*** (1.09e-06)	0.000180*** (9.22e-07)	6.83e-05*** (3.41e-07)
Vaccinated Flu (%)	0.000102*** (1.07e-06)	2.16e-05*** (9.23e-07)	3.02e-05*** (3.36e-07)
Air Pollution	6.70e-06*** (1.03e-06)	1.24e-06 (9.13e-07)	2.64e-07 (3.28e-07)
Housing Prob (%)	−0.000308*** (9.77e-07)	−0.000192*** (8.63e-07)	−4.85e-05*** (3.12e-07)
Constant	0.00112*** (3.42e-06)	0.000889*** (3.01e-06)	0.000232*** (1.05e-06)
Days-since-first-case FE	Yes	Yes	Yes
Observations	9,360,000	9,360,000	9,360,000
R-squared	0.981	0.991	0.971

Robust standard errors in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1.

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